Amendments to the Claims

The listing of claims will replace all prior versions, and listings, of claims in the application:

Listing of Claims:

1. Claim 1 (currently amended): A computerized method in decision system applications such as data mining, automatic process control, automatic target recognition, intelligent search, and machine vision for collecting global or population characteristics for decision tree regulation to achieve robust decisions in spite of the application dynamics and/or errors in training data comprises the following steps:
   (a) Means for inputting~~Input~~ a decision tree encapsulating the knowledge acquired from practical applications;
   (b) Means for inputting~~Input~~ a set of training samples;
   (c) Means for using~~Use~~ the training samples to determine a decision characteristic for at least one decision tree node, said decision characteristic selected from the group consisting of global characteristics and population characteristics calculating weighted global class training sample proportion of the at least one decision node wherein the decision characteristic regulates the decision tree for making robust decisions on new data in decision system applications.

Claims 2 - 3 (canceled).

Claim 4 (currently amended): The method of claim 1 wherein the global characteristics include global counts calculating weighted class training sample count for samples that are up to k layers above a node.

Claim 5 (canceled).

Claim 6 (currently amended): The method of claim 1 wherein the population characteristics include local population statistic calculating weighted class training sample proportion of the at least one decision node.

Claim 7 (currently amended): A computerized method in decision system applications such as data mining, automatic process control, automatic target recognition, intelligent search, and machine vision for classification regulation by information integration to achieve robust decisions in spite of the application dynamics and/or errors in training data comprises the following steps:

(a) Means for inputting~~Input~~ a decision tree encapsulating the knowledge acquired from practical applications;

(b) Means for inputting~~Input~~ a plurality of decision characteristics selected from the group consisting of global characteristics and population characteristics calculating weighted global class training sample proportion from at least one terminal node of the decision tree;

(c) Means for determining~~Determine~~ the confidence value for each of the plurality of said decision characteristics wherein the confidence value is defined as the ratio between characteristic value of a class and that of all classes;

(d) Means for determining~~Determine~~ an integrated confidence value for each class of said at least one terminal node wherein the confidence value integrates local and consistent global information for making robust decisions on new data in decision system applications.

Claims 8 - 9 (cancelled).

Claim 10 (currently amended): The method of claim 7 wherein the global characteristics and population characteristics are selected from the group consisting of

global counts, local counts, global population statistic, and local population statistic <u>calculating weighted class training sample proportion of the at least one terminal node of the decision tree</u>.

Claim 11 (currently amended): The method of claim 7 wherein the confidence value is selected from the set consisting of local count confidence, local population confidence, global count confidence and global population confidence <u>wherein the local count confidence for class c in a terminal node n is defined as</u>

$$\underline{LC_c^n = \frac{N_c^n}{\sum_{c \in All\_Classes\_in\_n} N_c^n}}$$

<u>the local population confidence for class c in a terminal node n is defined as</u>

$$\underline{LP_c^n = \frac{P_c^n}{\sum_{c \in All\_Classes\_in\_n} P_c^n}}$$

<u>the global count confidence for class c in a terminal node n is defined as</u>

$$\underline{GC_c^n = \frac{G_c^n}{\sum_{c \in All\_Classes\_in\_n} G_c^n}}$$

<u>the global population confidence for class c in a terminal node n is defined as</u>

$$\underline{GP_c^n = \frac{g_c^n}{\sum_{c \in All\_Classes\_in\_n} g_c^n}}.$$

Claim 12 (cancelled).

Claim 13 (currently amended): The method of claim 7 wherein the global characteristics have a global context coverage that is adjusted using different layer

depths wherein the global context is from layers above a node determined by the different layer depths.

Claim 14 (cancelled).

Claim 15 (currently amended): A computerized method in decision system applications such as data mining, automatic process control, automatic target recognition, intelligent search, and machine vision for decision tree pruning regulation by information integration to achieve robust decisions in spite of the application dynamics and/or errors in training data comprises the following steps:

(a) Means for inputting~~Input~~ a decision tree encapsulating the knowledge acquired from practical applications;
(b) Means for inputting~~Input~~ a set of training samples;
(c) Means for generating ~~Generate~~ a regulated measure selected from the group consisting of integrated confidence values and reliability measures comparing local, global, count and population confidences;
(d) For a non-terminal node of the tree having two descending terminal nodes, Means for determining~~determine~~ the accuracy values using the regulated measure under two separate nodes or combined node conditions;
(e) If combined node accuracy value is greater than the two separate node accuracy value, prune the terminal nodes by combing the two terminal nodes and converting the associated non-terminal nodes into one terminal node wherein pruned tree avoid over-fitting of data allowing robust decisions on new data in decision system applications.

Claim 16 (currently amended): The method of claim 15 wherein the reliability measures include a local population reliability measure R_{LP} defined as

$$R_{LP} = 1 - 2 * \left| \frac{LP_c^{\,n}}{(LC_c^{\,n} + LP_c^{\,n})} - 0.5 \right|.$$

Claim 17 (currently amended): The method of claim 15 wherein the reliability measures include a count reliability measure R_c defined as

$$R_c = 1 - 2 * \left| \frac{GC_c^{\,n}}{(LC_c^{\,n} + GC_c^{\,n})} - 0.5 \right|.$$

Claim 18 (currently amended): The method of claim 15 wherein the reliability measures include a population reliability measure R_P defined as

$$R_P = 1 - 2 * \left| \frac{GP_c^{\,n}}{(LP_c^{\,n} + GP_c^{\,n})} - 0.5 \right|.$$

Claim 19 (cancelled).

Claim 20 (currently amended): The method of claim 15 wherein the reliability measures include a global population reliability measure R_{GP} defined as

$$R_{GP} = 1 - 2 * \left| \frac{GP_c^{\,n}}{(GC_c^{\,n} + GP_c^{\,n})} - 0.5 \right|.$$

Claims 21 - 22 (canceled).

Claim 23 (currently amended): A computerized method in decision system applications such as data mining, automatic process control, automatic target recognition, intelligent search, and machine vision for decision tree generation regulation by information integration to achieve robust decisions in spite of the application dynamics and/or errors in training data comprises the following steps:

(a) Means for inputting~~Input~~ a set of training samples acquired from practical applications;

(b) For at least one node, means for generating~~generate~~a set of candidate thresholds;

(c) <u>Means for partitioning</u> ~~Partition~~ data at a candidate threshold;

(d) <u>Means for calculating</u> ~~Calculate~~ an evaluation function selected from the set consisting of integrated confidence value and reliability measures <u>comparing local, global, count and population confidences</u>;

(e) Repeat steps (c) and (d) for a plurality of partitions and select the partition for the node as the one that maximizes the evaluation function <u>wherein the partition for the node allows robust decisions on new data in decision system applications</u>.